Regional Scale Predictive Modelling in North-Eastern Germany

Benjamin Ducke[1]

[1] Heritage Management Brandenburg,
Wünsdorf, Germany
benducke@compuserve.de

Abstract. The paper presents a regional scale archaeological predictive model for the state of Brandenburg in North-Eastern Germany. The model incorporates more than 8,500 archaeological sites dating from the Mesolithic to the Slavic Middle Ages (ca. 8000 BC to 1250 AD) and a variety of environmental parameters. For the first time in the region, settlement patterns can be analysed and interpreted on a landscape scale. Developments in settlement structures and ecological dependencies can be tracked over almost 10.000 years. This knowledge is used to build a probability-driven predictive model using the Dempster-Shafer Theory of Uncertainty.

Keywords: Predictive Modelling, Heritage Management, Dempster-Shafer Theory of Uncertainty, GIS

1. Introduction

This paper describes the design, implementation and application of a predictive modelling tool for regional scale planning and analysis in the state of Brandenburg, North-Eastern Germany. Heritage management has been researching archaeological predictive models in the region for some years now, but so far only sample areas of very limited spatial extend have been modelled (see Münch 2003 for a detailed project description). The research presented in this paper was conducted to find out whether the available information can support analysis and prediction of archaeological sites for the area of the entire state (ca. 30,000 km^2). The basic ideas and troubles of archaeological predictive modelling itself will not be discussed in this paper. Please refer to van Leusen et al. (2004) for a summary or browse CAA proceedings for recent developments.

Epoch		S	G
Mesolithic	8000–5500 BC	152	0
Neolithic	5500–2200 BC	421	90
Bronze Age	2200–800 BC	1513	1986
Iron Age	800–50 BC	924	597
Germanic Age	50 BC–375 AD	763	219
Age of Migrations	375 AD–750 AD	38	7
Slavic Middle Ages	750 AD–1250 AD	1617	113

Table 1. Number of prehistoric settlements (S) and graves (G) in Brandenburg.

There is no comprehensive assessment of the state's current archaeological record, which consists of ca. 27,000 sites. Not all of them have revealed enough clues to determine their age and function. About 8,500 sites can be attributed to prehistoric settlements or graves and have thus been included in this study. All of Brandenburg's main archaeological epochs are represented with more or less sufficient site numbers. Due to the glacial history of the landscape, human remains and artefacts dating before the last Ice Age are virtually absent and thus the record starts with the Mesolithic (Tab. 1).

Knowledge about Brandenburg's prehistoric settlement structures is generally fragmentary and limited to local observations. It is hoped, therefore, that this study may provide some fundamental information and research perspectives needed to establish a landscape and environmental archaeology in Brandenburg.

2. Predictive Model Design

2.1 Fundamental Issues

According to current design practice, a predictive model calculates a value of "archaeological importance" for each cell of a regular raster overlaid on the landscape. The calculation is based on correlations between known archaeological site locations and variables that can be used to describe them, most commonly 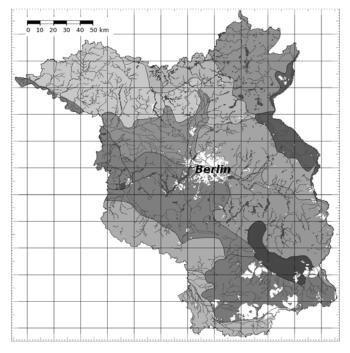topographical, hydrological and geological data. Before the model could be set up, several fundamental design issues had to be considered, one of them being the question what mathematical framework to use. A quick review of the current state of the art (e.g. van Leusen et al. 2004) shows that statistical methods, especially statistical regression models, are still the most widely used tools in archaeological predictive modelling. It was found, however, that a generalised probability model would offer the best combination of generality, robustness and flexibility (see next section for details). Another concern was the fact that some digital geodata layers were only available with low resolution but nevertheless had to support a target cell width (ground resolution) of 50 m in order for the model to be of any use in detailed heritage management planning. In the end it turned out, however, that all data was of sufficient detail and quality. Deciding what information to include depends on what information is available, expected to be relevant and of good enough quality to support the needed precision. From the digital map material available for the state of Brandenburg, a soil type map, a digital elevation model and a map of buffered stream networks were chosen. From these, the following

information layers could be retrieved: height, slope, aspect, basic morphology (plain, ridge, pit etc.), terrain curvature, buffered distance from rivers of 1st to 7th degree, buffered distance from large, medium and small lakes and buffered distance from known sites.

Terrain parameters such as height, slope and aspect undoubtedly have relevance for site location, as does the basic type of morphology. All of them can be derived from a high-quality digital elevation model with standard GIS tools. Terrain curvature, although important for estimating effects of erosion on site preservation (Ducke 2004) was found not to be relevant and excluded from the analysis. Aspect, i.e. the direction of the slopes on which the sites lie, showed barely enough relevance to be included in the study (sites seem to have a little preference for slopes facing east and south-east). Differentiation of water distances according to the type of stream improves model quality, although experiments have shown that the same buffer size (500 m) can be applied to any type of water body.

In accordance with Waldo Tobler's first law of Geography, which states that "all things are related, but nearby things are more related than distant things" (Tobler 1970), it has been observed that the neighbourhoods of known sites are especially likely to produce more sites. To compensate for this spatial autocorrelation, a layer with a buffer of 500 m around a randomised sample of the known sites could be included as additional evidence for site presence.

For obvious reasons, the validity which can be achieved by such a model also depends on the quality of the archaeological data itself. Unfortunately, the latter is often very limited. In order to avoid extremely high variation and over-generalisation of archaeological data, the study area was split up into 13 regions as defined by their distinctive historical geography (Fig. 1), each of them with characteristic archaeological and topographical properties. The predictive

Fig. 1. The study area of Brandenburg (North-Eastern Germany). 13 subdivisions are shown in different colours.

model was then run for each region separately and the results patched together.

2.2 Mathematical Framework

For the mathematical framework, the Dempster-Shafer Theory of Evidence (DST) was chosen. DST, as defined by Dempster (1967) and Shafer (1976), is built around the central concept of *belief*, which is a somewhat more relaxed, generalised version of mathematical probability. In fact, DST itself is a generalised probability theory that has a lot in common with Bayesian Probability Theory but is less strict and more simple to use. In analogy to probabilities in a Bayesian analysis, DST assigns a strength of belief to hypotheses within a *frame of discernment* (FOD). The FOD for a simple archaeological predictive model consists of two mutually exclusive hypotheses which cover all possibilities:

h_1 = "site" and h_2 = "no site".

In a Bayesian analysis, there is a fundamental summation property $p(h_1) + p(h_2) = 1$. Hypotheses are thus "linked" to each other: every observation which supports "site" refutes "no site": $p(h_2) = 1 - p(h_1)$ and vice versa. This contradicts real life experience. Clearly, the reasons that made prehistoric settlers choose a site location might have been completely different from those that caused them to avoid certain spots. DST caters for this by automatically creating a third, implicit hypothesis $h_{1,2}$ which contains *uncertainty*, i.e. all evidence that might support h_1 and h_2 equally well (note h_1 and h_2 cannot both be refuted because of the requirement that they must cover all possibilities).

In addition, there is a number of *evidences* that might support or refute each hypothesis: soil type, topography, distance from water etc. Evidences are encoded as classified GIS raster maps with value range [1...*n*] and *n* being the highest class number. An evidence is quantified by a *basic probability assignment* (BPA), which assigns a probability value m to each hypothesis, such that:

$$m(h_1) + m(h_2) + m(h_{1,2}) = 1.$$

Calculation of BPAs for a given evidence map could be done in a number of ways. The solution adopted in this study is to simply compare the overall frequency of a given class F_1 (e.g. "soil type A" or "height 1 to 10 m") in an evidence raster map to the frequency with which this class occurs in cells that also contain known archaeological sites (F_2). If $F_2 > F_1$ then the evidence supports the "site" hypothesis and vice versa. To compensate for hidden variables and insufficient data quality, a user-specified percentage of the BPA mass may also be shifted to the "uncertainty" hypothesis. Every raster map that is to be included as evidence in the DST analysis must thus be turned into three separate maps, quantifying $m(h_1)$, $m(h_2)$ and $m(h_{1,2})$ respectively, with each cell summing to 1 if they are overlaid.

Once all evidences have been cast into this form, they can be combined using Dempster's Rule of Combination (see Smets 1994 for mathematics, Ejstrud 2004 for an application in

archaeology). This results in a number of interesting metrics, the most important one of them being "belief". Their usefulness will be discussed in the next section.

In Summary, the following properties make DST a very useful tool for building predictive models:

- Simple, "natural" terminology, concepts and usage.
- Handling of uncertainty.
- Few mathematical constraints.
- Provides very useful metrics for the output maps.

Naturally, there are also some drawbacks:

- The variety of output metrics can make it hard to find the most useful map.
- Mathematical properties not as well explored as classical probability theory.
- DST is not very well documented.
- Few software implementations exist (but see below).

2.3 Software Implementation

Although there are few software packages available which provide DST functionality in a GIS environment, this is not the first time it has been used in predictive modelling.

A solution using ArcGIS was published a while ago (Lorup 1999) and the Idrisi GIS system has a (somewhat limited) DST module which even features archaeological examples in its documentation (Eastman 1997). The latter software has been used with success by Ejstrud (2004) in his studies on archaeological predictive modelling in Denmark. Ejstrud could demonstrate the superiority of a belief-based predictive model in comparison with a statistical regression model.

Nevertheless, it was found that existing software did not harness the full power of DST and was only available in closed source, commercial GIS packages. Thus, a custom set of modules was created for the open source GRASS 5 GIS platform and will hopefully be available soon as part of the GRASS 5.3 and 5.7 source code distributions (see GRASS GIS). The modules include programs for randomised sampling, site distribution analysis, raster map classification, automated BPA quantification and the core DST combination modules. With their help, any sort of evidence encoded in raster GIS layers can be included in the DST analysis. All of the work presented in this paper was carried out using this open source software.

3. Running the Predictive Model

A possible workflow of a DST predictive modelling analysis within a GIS is:

- Take a randomised site sample.
- Produce evidence maps (BPAs) from sample site locations and raster coverage maps (soil, topography etc.).
- Combine evidence maps using Dempster's Rule of Combination.
- Compare result maps with full set of samples:
  a. If too many sites fall in 'no site' areas: repeat from step 2 but transfer more BPA mass from the 'site' to the 'uncertainty' hypothesis and/or include further evidence.
  b. If the 'site' areas seem to be too large: repeat from step 2 but transfer more BPA mass from the 'no site' to the 'uncertainty' hypothesis and/or include further evidence.

This process yields several output maps with values in the range [0;1] that can be used for decision support and interpretation. The most basic one is the *belief* map which is akin to probability and represents the strength of belief in a hypothesis ("site" or "no site") being true. Another useful metric is *plausibility* which represents the highest possible belief assuming that there was no uncertainty. The *belief interval* map shows the differences between plausibility and belief and can be used to identify "hot spots" of uncertainty and areas where more research could improve the situation. Finally, the *weight of conflict* can identify places in which evidences contradict each other and guide a researcher in deciding which variables to include in the analysis.

3.1 Predictive Models as Exploratory Tools

As has been mentioned before, this predictive model was the first research effort ever to include all of the state's archaeological record and study the patterns of site distribution through time. In the course of this, it became clear that predictive models can also act as very powerful exploratory tools. They enable researchers to study interactions between site locations and landscape variables of any type on any scale and facilitate insight into complex relationships.

This process starts at the very first stage of building the model, as a thorough exploratory data analysis is required to create meaningful evidence maps. As an example, consider the phenomenon of site autocorrelation mentioned in section 2.1. To turn this information into an evidence raster map, several questions have to be answered:

- What sites correlate with each other?
- What is the extent of the spatial correlation?
- In how far is there a difference between archaeological epochs?

A statistical analysis using random samples of 10, 25 and 50% of the known sites revealed a lot of interesting relationships. For example, it can be demonstrated that a random sample of about 600 settlement sites is good enough to estimate the positions of almost half the known sites for Brandenburg's entire 30.000 km^2 if we add a buffer zone of 2 km radius around the sample sites. Even though the buffer zones account for less than 10% of the territory! This shows that there is strong spatial correlation in the settlement site locations. Settlers obviously did not like to relocate far from well-known and established nuclei.

Grave distribution seems to follow different trends depending on the archaeological epoch. Bronze Age graves show the same spatial correlation properties as settlements in general, Iron Age graves do not.

All of these facts have to be considered when creating a buffer zone map for use as autocorrelation evidence.

The situation is not less complex for any of the other evidences listed in section 2.1. A solid predictive model is

thus far from being an automatic, purely data-driven tool. On the contrary, it represents deep and – at least in the case of Brandenburg – pioneering understanding of settlement patterns, human and environmental processes.
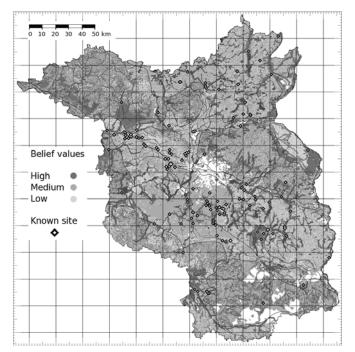
3.2 Brandenburg Through the Ages

An obvious means of gaining insight into prehistoric settlement processes is to compare predictive maps of different archaeological epochs. Provided that the archaeological data is of sufficient quality, it should be possible to find plausible explanations for observed changes in site patterns over time. With the limitation of course, that all interpretations will only be partially true, as a predictive model at this scale can never include all relevant variables and there will always be uncertainty involved. However, even though not all site locations can be explained with the relatively crude environmental variables included in this model, it is still possible to account for a large portion of them and to identify general trends in the diachronic comparison.
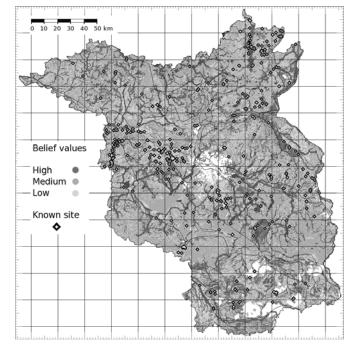
To demonstrate the potential, we will take a brief look at the settlement site patterns.

The map for the Mesolithic (Fig. 2) shows a pattern of sites which follow the courses of the main navigable rivers. Apparently, mesolithic settlers did not dwell in the "chaotic", densely forested interior. It should be noted however, that the number of known mesolithic sites is too small in almost all parts of the study area for reliable statistics. Only in the central-western part of Brandenburg can this model be backed by sufficient data.

The pattern of Neolithic settlement sites (Fig. 3) shows a spread of activities from the main Elbe and Oder rivers (the two major sources of neolithic influx into Brandenburg) into the country's interior. Settlement sites can be found with equal

Fig. 3. Belief values for hypothesis "site" in the Neolithic (settlements). Red = high belief; green = medium belief, yellow = low belief.

frequency along the banks and shores of larger and smaller streams and lakes. A much more significant indicator – owing to the neolithic economy – is soil quality. Most sites lie on fertile clay and peaty soils.

This parameter is still important, but a little less dominant in the Bronze Age (Fig. 4) which sees technological changes and advances that lead to a foundation of settlements in formerly less attractive areas. In fact, it is only in the Middle Ages that Brandenburg develops another system of settlements as dense
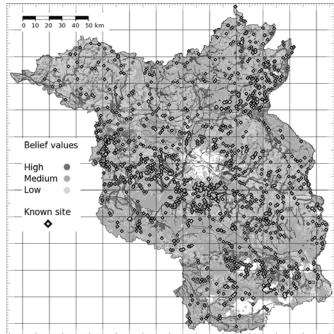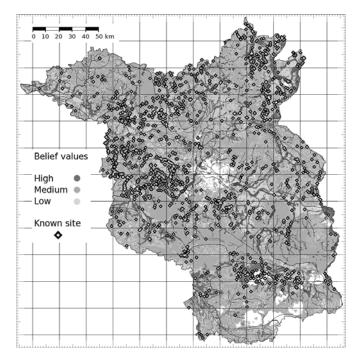

Fig. 2. Belief values for hypothesis "site" in the Mesolithic (settlements). Red = high belief; green = medium belief, yellow = low belief (here shown with different grey levels).

Fig. 4. Belief values for hypothesis "site" in the Bronze Age (settlements). Red = high belief; green = medium belief, yellow = low belief (here shown with different grey levels).

Fig. 5. Belief values for hypothesis "site" in the Slavic Middle Ages (settlements). Red = high belief; green = medium belief, yellow = low belief (here shown with different grey levels).

as that of the Bronze Age. Predicting site locations is accordingly difficult, as there is no single environmental variable which they submit to. This situation is reflected in the absence of large, coherent patches of "high belief" values for the "site" hypothesis.

Other variables that quantify social, political etc. processes would be needed but are not currently available. The situation does not change much in the Iron Age and Germanic Age. The Age of Migrations is a period of settlement caesura that hasn't so far revealed enough sites to justify a quantitative analysis. The Slavic Middle Ages, interestingly enough, exhibit a site pattern and predictive model structure that seems to resemble the Mesolithic at first glance (Fig. 5). This is caused by the fact that the main navigable rivers are again becoming a major factor – this time as links in a medieval trade network that spans all of Europe.

Much more remains to be said, e.g. about grave locations and the topographical relationships they adhere to, but owing to the limited space, these examples must suffice to show the potentials of the model.
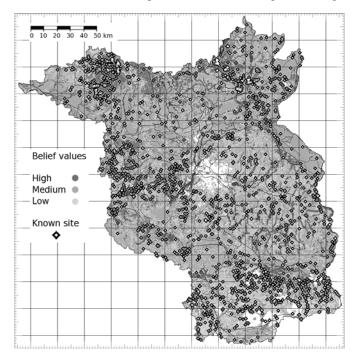
3.3 Methodological Limitations

As has been mentioned before, interpretations of the model output always depend on the quality and detail of the archaeological data. In this case, the most severe limiting factor is the lack of temporal resolution. This is obvious e.g. for the "Neolithic", which includes several "cultures" with diverse settlement patterns and environmental conditions, from the first neolithic settlers to the dawn of the Bronze Age. As concerns the latter, a good indication of the possible confusions caused by low temporal resolution can be found in the grave locations belief map (Fig. 6). Looking at it, it becomes immediately apparent that the Northern rim of the

study region shows coherent patches of deep red. This indicates that a portion of the Bronze Age graves were erected in locations which can be clearly identified by significant variables, in this case a topographical position that favors high altitude and visibility. Further south, the picture gets more fragmented and most of the graves are in fact located in the yellow area of medium strength belief. There seems to be no variable in the model which could reliably explain this "chaotic" pattern. This remarkable division did, however, never exist at one time in actual history. The picture can only be explained if one takes into account that it represents the intermingling of grave sites from two different epochs within the Bronze Age. The northern-most part of Brandenburg is dominated by burial mounds of the 16th to 14th centuries BC which were erected in imposing topographical locations. Further south, the majority of the record is made up of literally thousands of urnfield culture (ca. 12th to 8th century BC) pit graves that often agglomerate in large burial grounds.

Apart from archaeological data quality, the most regrettable lack of information in the current model concerns modern land use and impact assessment. Some studies have been conducted in the past (see Ducke 2004) but only for a small sample area. There is currently no sufficient digital data to support erosion assessment and site impact management for the entire state.

4. Results

Examination of data from more than 8500 sites has, for the first time in the region, revealed large-scale patterns of change and consistency in the region's prehistoric settlement structures. We are now able to compare settlement patterns and create models to explain them. Archaeological heritage

Fig. 6. Belief values for hypothesis "site" in the Bronze Age (graves). Red = high belief; green = medium belief, yellow = low belief (here shown with different grey levels).

management now has a tool to use in large-scale planning processes. The output maps can be presented to developers and used in negotiations and resource allocation.

The project has shown that it is possible to get significant information about site distributions on a landscape scale and use them in a predictive model. In the future, improved archaeological data will allow for finer grained spatial and temporal resolution. This will allow more significant observations to be made from the site samples. It is also hoped that better archaeological data will improve the certainty with which the model classifies unknown locations. Also, processes affecting site preservation will have to be taken into account.

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